The Relation between Price Changes and Trading Volume: A Study in Indian Stock Market

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ABSTRACT

This study investigates the dynamic relationship between stock return and trading volume of Indian stock Market by using Bivariate Regression model, VECM Model, VAR, IRF and Johansen's Co integration test. The study shows that there is a bi-directional causality between trading volume and stock return volatility. Again the study used Variance Decomposition technique to compare the degree of explanatory power of the trading volume over stock return and the evidence supports the influential role of the trading volume in the Indian stock market. Further Johansen's co integration analysis demonstrates that stock return is co integrated with the trading volume indicating long-run equilibrium relationship. The study concludes that stock price changes in any direction have information content for upcoming trading activities.

Keywords: *Stock Returns, Trading Volume; Causality, Johansen's Co integration*

INTRODUCTION

The relationship between stock returns and volume has been widely documented in finance literature. Karpoff (1987) provides a good review of literature and explains that this relationship provides insight into the structure of financial markets and is important for event studies for drawing inferences from the use of price and volume in analysis. Numerous papers have documented the fact that high stock market volume is associated with volatile returns. It has also been noted that volume tends to be higher when stock prices are increasing and vice-versa. The concept of the volume impact is built on the fact that price needs volume to move, thus, the high volatility of stock prices may be produced as consequence of volume volatility and trading activities. However, since investors are heterogeneous when interpreting new information, stock returns may stay unchanged even though new information is brought to the market. On the other hand, stock returns may only change if there is positive trading volume. As it happens with returns, trading volume and its changes mainly reflect the available set of relevant information perceived by the market. A large segment of the finance literature investigates the link between information and prices. Theory suggests that prices are function of public information and order flow (see, for example, Grossman and Stiglitz (1980) and Glosten and Milgrom (1985)).Order flow is driven by both public and private information as well as investor shocks, which may be either rational (e.g., no information-based liquidity trades) or irrational (e.g., trades based on noise as described by Black (1976)). Prices can deviate from fundamental value due to market microstructure, liquidity, and hedging effects. Pricing errors can arise from noise trading and due to under reaction or overreaction to information. So, in this context, deeper understanding of the role of trading volume and relationship with stock return may help investors to identify future patterns of the stock market which can be used in their investment decisions. Secondly Stock price-volume relation can also be used as basis of trading strategy for efficiency of stock markets. Thirdly, the relationship between stock price and volume can be used to examine the usefulness of technical analysis. However, there is little study is made in India during Asian crisis and world stock market crisis period 2005-2010 .This motivate us for exploring research in Indian Stock Market to determine the role of trading volume and volatility in the dynamics of price discovery process in India. So, in this paper, we have raised three research question .First this paper will add to the existing literature by providing robust result. Secondly we investigate the causal relationships between return volatility and trading volume in Indian stock market. We also use Vector Auto regression (VAR) model to examine the short run causality between stock price and volume. Thirdly, we have used Johansen's Co integration test to determined the long-run relationship between stock return and volume in India to obtain new insights. Therefore, the present work improves the earlier studies and offers a value addition to the existing literature and proves to be useful to the investors as well as regulators. The rest of the paper proceeds as follows: In section two we provide a brief review of past literature relating to the causal relationship between stock returns and trading volume. Section three describes the data & methodology used in the study. Section four discusses the empirical findings while the last section offers some concluding observation.

LITERATURE REVIEW

The discussion in literature on price and volume relationship has been approached from various perspectives, which include the relation between price changes and volume (Epps and Epps, 1976), absolute price changes and volume (Clark, 1973; Wood et al. 1985), causal relationship between price and volume (Wang, 1994; Ciner, 2002), and trading volume and conditional volatility (Lamoureux and Lastrapes, 1994). These studies demonstrated that trading volume is positively related to stock prices. Hiemstra and Jones (1994) used nonlinear Granger causality tests to examine the nonlinear causal relation between percentage changes in the NYSE trading volume and daily Dow Jones Stock Returns and found that there is a positive nonlinear bidirectional relationship between returns and volume. Bhagat and Bhatia (1996) also employed daily data to test the causal relationship between volume and return, finding return causes volume but not vice versa. Basci et al (1996) used weekly data on 29 individual stocks in Turkey and found the price level and volume is co integrated. Saatcioglu and Starks (1998) used monthly data from six Latin American stock markets to test the relation between price changes and volume, found a positive price-volume relation and a causal relationship from volume to stock price changes but not vice versa. Chordia and Swanminathan (2000) found that past trading volume can be used to predict future stock price momentum. Ratner and Leal (2001) examined the Latin American and Asian financial markets and found a positive contemporaneous relation between return and volume in these countries except India. At the same time they observed that there exists a bi-directional causal relation between return and volume. In summary, the return and volume are strongly related contemporaneously but there is little evidence that either can be used to predict the other. De Medeiros and Doornik (2006) investigated the empirical relationship between stock returns, return volatility and trading volume in Brazilian stock market and found the support for a contemporaneous as well as dynamic relationship between stock returns and trading volume. Zolontoy and Melenberg (2007) studied the dynamic relationship between trading volume, volatility, and stock returns at the international stock markets and their findings suggested the importance of the trading volume as an information variable. Sabri (2008) found that the volume-stock price movements are significantly integrated for all selected markets.

TIME SERIES DATA &METHODOLOGY

Bombay Stock Exchange is the oldest stock exchange in Asia and today, it is the world's 5th most active in terms of number of transactions handled through its electronic trading system. It is also in the top ten of global exchanges in terms of the market capitalization of its listed companies.BSE have facilitated the growth of the Indian corporate sector by providing with an efficient capital raising platform. The BSE Index, SENSEX, is India's first and most popular Stock Market Benchmark Index. So we have taken BSE sensex for our study. Similarly trading volume refers to the number of shares traded during a defined time period. When investors or financial analysts see a large increase in volume, it may indicate a significant change in the price of security. Significant volume spikes may indicate some kind of important news taking place in the stock market. We have taken trading volume as another variable to determine its impact on stock market as well. The required time series data is based on daily closing price of BSE SENSEX, actively traded 30 scripts and Trading volume have been collected from Bombay Stock Exchange for a period of five years from January 2005 to January 2010. We have chosen the data period 2005 to 2010 because during this period Indian stock markets have undergone substantial policy changes characterized by the revival of private foreign capital flows to emerging market economies, flexible exchange rates, strong economic growth, credit market crisis in the United States and sharp fell in Asian market. These changes have affected the movement of index and magnitude of volume trades in the market in different ways. Returns are proxied by the log difference change in the price index. The stock return is calculated as the continuously-compounded return using the closing price:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100\%$$

Where ln (P_t) denotes the natural logarithm of the closing price at time t

Prior to modeling any relationship, non-stationarity must be tested. Stationarity means that the mean and variance of the series are constant through time and the auto covariance of the series is not time varying (Enders, 2004). For application of granger causality test, VAR model and Impulse Response Function, the initial step in the estimation involves the determination of the times series property of each variable individually by conducting unit root tests. For the purpose of this study, we use the model proposed by Augmented Dickey Fuller (ADF) test, Phillip-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test.

ADF (Augmented Dickey-Fuller) Test

The unit root test is carried out by using the Augmented Dickey Fuller (ADF) test. The mathematical expression of the ADF test for trend is

$$\Delta y_t = \alpha + \phi\Gamma + (1-\beta)Y_{t-1} + \sum_{t=1}^{n} \lambda \Delta Y_{t-p} + \varepsilon_t$$

Yt is the variable tested for unit root and Δ is the first difference operator; β is the constant term; T is the time trend and n is the lag number. If the series is stationary then (1- β) =1, and against this, if model detect non stationarity in data series then (1- β) < 1. So the hypotheses of our study are: H_0 Time series is stationary and H_1 Time series is nonstationary. The null hypothesis of the study is rejected if the statistical value is lesser than the critical value and data series will be considered as non stationary (following the random walk). This implies that Yt is non-stationary and does not contain unit root.

PP Test

To make up for the shortcomings of the ADF test we used the Phillips-Perron test, which allows the error disturbances to be weakly dependent and heterogeneously distributed.Further unit root test is carried out using the Phillip-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test, so as to validate the result of ADF test. The mathematical expression of the PP test is;

$$\Delta y_t = \alpha Y_{t-1} + X_t \phi + \varepsilon_t$$

Where Yt is the stock price index tested for unit root. Xt are optional exogenous regressors that could either be trended or none trended. ϕ are the parameters to be estimated and ε_t are the error terms. The null and alternative hypothesis of this test is

Ho: α =0 and H_1 = α > 0

The null hypothesis that the stock price index does not contain unit root is accepted when the test statistic is less than the critical value at the selected level of significance.

KPSS (Kwiatkowski, Phillips, Schmidt, and Shin) Test

In the KPSS test, stationarity is the null hypothesis and the existence of a unit root is the alternative. KPSS tests are used for testing a null hypothesis that an observable time series is stationary around a deterministic trend. The series is expressed as the sum of deterministic trend, random walk, and stationary error, and the test is the LM test of the hypothesis that the random walk has zero variance. KPSS type tests are intended to complement unit root tests, such as the ADF tests. The KPSS tests is shown by the following equation

$$y_t = x_t^1 \beta + \mu$$

The LM statistics is given by:

$$LM = \sum_{t=1}^{T} s^2 t / \sigma_t^2$$

Where, σ_t^2 is an estimator for the error variance. This latter estimator σ_t^2 may involve corrections for autocorrelation based on the Newey-West formula. In the KPSS test, if the null of stationarity cannot be rejected, the series might be co integrated. The KPSS test is estimated and found to contain a unit root when the test statistics is less than the critical values at the estimated level of significance.

Stock Returns and Trading Volume

To test the contemporaneous relationship between stock returns and trading volume, we apply the multivariate model proposed by (Lee; Rui, 2002):

$$R_t = \alpha_o + \alpha_1 V_1 + \alpha_2 V_{t-1} + \alpha_3 R_{t-1} + u_t$$
$$V_t = \beta_o + \beta_1 R_1 + \beta_2 R_{t-1} + \beta_3 V_{t-1} + v_t$$

R_t and V_t are stock return and trading volume respectively. α_1 and β_1 are model parameter and u_t and v_t are white noise error term.

It is often reported that price fluctuations tend to increase if there is high trading volume, especially in times of bullish markets. It may happen due to relation between higher orders moments of stock returns and trading volume. We scrutinize this by extending a model which relates trading volume to squared stock returns by the following regression (Brailsford. 1996):

$$V_t = \alpha_o + \phi_1 V_{t-1} + \phi_2 V_{t-2} + \alpha_1 R_t^2 + \alpha_2 D_t R_t^2 + e_t$$

Where D_t is a dummy variable that equals to 1 if the R_t is positive and 0 if R_t negative. The estimated parameter α_1 measures the relationship between return volatility and trading volume irrespective of the direction of price change. The estimated parameter α_2 measures the degree of asymmetry in that relationship.

Co integration Test

Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary linear combination exists, the non-stationary time series are said to be co integrated. The purpose of the co integration test is to determine whether a group of non-stationary series is co integrated or not. The presence of a co integrating relation forms the basis of the VEC specification. After identifying the order of integration, we then use the Johansen's (1991, 1995a) co integration test to determine whether there is a long-run relationships between the various series. The Johansen's technique for estimating co integration is superior because it is based on well-established maximum likelihood procedure that provides test statistics to determine number of co integration vectors as well as their estimates. The existence of more than one co integrating vector implies higher stability in the system.

The co integration testing procedure suggested by Johansen's (1991, 1995a) to test the restrictions imposed by co integration on the unrestricted VAR involving the series.

Considering a VAR of order ___:

$$Y_t = A_1 Y_{t-1} + -------- ApY_{t-p} + BX_t + \varepsilon_t$$

Where Y_t is a K-vector of non-stationary 1(1) variable, X_t is a d vector of deterministic variables and ε_t is a vector of innovations. It can rewrite the VAR as

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i-1}^{p-1} T_i \Delta Y_{t-1} + BX_t + \varepsilon_t$$

$$Where \Pi = \sum_{i-1}^{p} A_{t-1}, T_i = \sum_{j-i+1}^{p} Aj$$

Granger's representations theorem asserts that if the coefficient matrix Π has reduced rank r<k, then there exist Kr matrixes and α & β each with rank r such that Π=αβ' is stationary r is the number of co integrating relations and each column of is the co integrating rector. The elements of α are known as the adjustment parameters in the vector error the Π matrix in an unrestricted form. The Johansen approach to co integration test is based on two test statistics, viz., the trace test statistic, and the maximum Eigen value test statistic.

Trace Test Statistic

The trace test statistic can be specified as: $\tau_{trace} = -T \sum_{i=r+1}^{k} \log(1-\lambda_i)$, where λ_i is the ith largest Eigen value of matrix Π and T is the number of observations. In the trace test, the null hypothesis is that the number of distinct co integrating vector(s) is less than or equal to the number of co integration relations (r).

Maximum Eigen value Test

The maximum Eigen value test examines the null hypothesis of exactly r co integrating relations against the alternative of $r+1$ co integrating relations with the test statistic: $\tau_{\max} = -T\log(1-\lambda_{r+1})$, where λ_{r+1} is the $(r+1)^{th}$ largest squared Eigen value. In the trace test, the null hypothesis of $r=0$ is tested against the alternative of $r+1$ co integrating vectors.

It is well known that Johansen's co integration test is very sensitive to the choice of lag length. So first a VAR model is fitted to the time series data in order to find an appropriate lag structure. The Akaie Information Criterion (AIC), Schwarz Criterion (SC) and the Likelihood Ratio (LR) test are used to select the number of lags required in the co integration test.

Vector Error Correction Model

Once the co integration is exist between variables then the next step requires the construction of error correction mechanism to model dynamic relationship. The purpose of the error correction model is to indicate the speed of adjustment from the short-run equilibrium to the long-run equilibrium. A vector error correction (VEC) model is a restricted VAR designed for use with nonstationary series that are known to be cointegrated. The VEC has cointegration relations built into the specification so that it restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

Co integration implies that the transitory components of the series can be given a dynamic error correction representation; one that allows for flexibility in the short-run dynamics but constraints the model to return to long-run equilibrium (see Engle and Granger, 1987). If there is evidence of a co integrating relationship, causal inferences can be made by estimating the parameters of the following vector error correction model (VECM) equation. The VECM model allows us to differentiate between the short- and long-run dynamic relationships, and tests for the hypothesis that the coefficients of lagged variables and the error correction terms calculated from the co integrating regression are zero. If the coefficients in the system are jointly significant, then the lagged variables in the system are important in predicting current movements of the dependent variables (i.e., the short run dynamics), and the dependent variables in the equation adjust to the previous period's equilibrium error.In this paper the error correction model as suggested by Hendry has been used. The general form of the VECM is as follows:

$$\Delta X_t = \alpha_0 + \lambda_1 EC_{t-1}^2 + \sum_{i=1}^{m} \alpha_i \Delta X_{t=i} + \sum_{j=1}^{n} \alpha_j \Delta Y_{t-j} + \varepsilon_{1t}$$

$$\Delta Y_t = \beta_0 + \lambda_2 EC_{t-1}^2 + \sum_{i=1}^{m} \beta_i \Delta X_{t=i} + \sum_{j=1}^{n} \beta_j \Delta X_{t-j} + \varepsilon_{2t}$$

Where Δ is the first difference operator; EC_{t-1} is the error correction term lagged one period; λ is the short-run coefficient of the error correction term ($-1<\lambda<0$); and ε is the white noise. The error correction coefficient (λ) is very important in this error correction estimation as greater the co-efficient indicates higher speed of adjustment of the model from the short-run to the long-run.

The error correction term represents the long-run relationship. A negative and significant coefficient of the error correction term indicates the presence of long-run causal relationship. If the both the coefficients of error correction terms in both the equations are significant; this will suggest the bi-directional causality. If only λ_1 is negative and significant, this will suggest a unidirectional causality from Y to X. Similarly, if λ_2 is negative and significant, this will suggest a unidirectional causality from X to Y. On the other hand, the lagged terms of ΔX_t and ΔY_t appeared as explanatory variables, indicate short-run cause and effect relationship between the two variables. Thus, if the lagged coefficients of ΔX_t appear to be significant in the regression of ΔY_t, this will mean that X causes Y. Similarly, if the lagged coefficients of ΔY_t appear to be significant in the regression of ΔX_t, this will mean that Y causes X.

To examine the contemporaneous relation between stock returns and trading volume, we have used Granger Causality Test. The Granger Causality test is used to investigate whether the past information of volatility is useful to improve the prediction of trading volume and vice versa. We test whether trading volume causes return or return causes trading volume by employing bivariate VAR model. This study relies on the conventional F-test for joint exclusion restrictions.

Variance Decomposition (VDC) and Impulse Response Function (IRF)

The VAR by Sims (1980) has been estimated to capture short run causality between stock return and trading volume. Various decomposition and impulse response function has been utilized for drawing inferences. The VDC is an estimate of the proportion of the movement of the n-step ahead forecast error variance of a variable in the VAR system that is attributable to its own shock and that of another variable in the system. Similarly, the IRF shows impulse responses of a variable in the VAR system to the time path of its own shock as well as that of the shock to another variable in the system. While impulse response functions trace the effects of a shock to one endogenous variable to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Thus, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR.

EMPIRICAL FINDINGS

Unit Root Tests:

The study here employs the unit root test to examine the time series properties of concerned variables. For the test of unit root the present study employees the Augmented Dickey Fuller test, PP test and KPSS test. The table 1 reports that the value of ADF test of all variable is less than its critical values at 1%, 5% and 10% respectively. Therefore the study rejects the null hypothesis and concludes that data series is non-stationary and following the random walk. The statistical values of DF-GLS, PP and KPSS are also lesser than their corresponding critical values and rejecting the null hypothesis of stationarity.

Table 1 goes here

Descriptive Statistics

The basic descriptive analysis of the time series of stock returns and trading volume is shown in Figures 1,2and table 2. All returns are calculated as the first difference of the log of the daily closing price. Daily trading volume and stock return have positive kurtosis and high JB statistics that implies that the distribution is skewed to the right and they are leptokurtic((heavily tailed and sharp peaked), i.e., the frequency distribution assigns a higher probability to returns around zero as well as very high positive and negative returns. The Jarque – Bera statistic test indicates that the null hypothesis of normality is rejected and shows that all the series exhibit non-normality. Squared value of daily stock return is used to proxy return volatility.

Figure 1 goes here

Figure 2 goes here

Table 2 goes here

Contemporaneous relationship between stock returns and trading volume

Table 3 indicates the Contemporaneous relationship between stock returns and trading volume. The parameter α_3 is significant at the 1% level and it is positive. There is no evidence of lagged relationship between stock returns and trading volume, since the parameter α_2 is positive but insignificant. However, the contemporaneous relationship between stock returns and trading volume is not simultaneous, since the parameter α_1 is not significant, which means that R depends on V, but V does not depend on R. The strong time dependency of trading volume is documented by highly significant parameters β_2 and β_3 which is depicted in the following table 4.

Table 3 goes here

Table 4 goes here

Again we examined the relation between higher order moments of stock returns volatility and trading volume. So we extend the model which relates trading volume to squared stock return (Brails ford, 1996).Table-5 reported that parameter α_1 is positive and highly significant at 1%level indicating relationship between return volatility and trading volume irrespective of the direction of the price changes. It suggests that higher trading volume is associated with an increase in stock return volatility. The parameter α_2 is insignificant suggesting that there is asymmetry relationship between return volatility and trading volume. The analysis points out that news is having impact on trading volume. So, good news increasing the stock return volatility lead to increase trading volume and bad news decrease the stock return volatility and reducing the trading volume.

Table 5 goes here

Table 6 goes here

Table 6-a goes here

Table 6-b goes here

The table – 6 indicated one co integrating vector at 5% level of significance. So it rejects the null of no co integration at the conventional level of significance and indicates that stock return is co integrated with the trading volume and has a long-run equilibrium relationship with it. However, it is possible that co integrating variables may deviate from their relationship in the short run, but their association would return in the long run.

Table 7 goes here

Using a VECM for the period January 2005 through January 2010, the estimated results Shown in Table 7, suggest that the long-run elasticity of the Indian stock market to the trading volume is almost 16.81. In other words, a one percent deviation in the trading volume decreases the stock return by 16.81 percent. The negative statistically significant value of error correction coefficient indicates the existence of a long-run causality between the stock return volatility and trading volume of the study.

Table 8 goes here

The table 8 exhibits that there is bi-directional causality between trading volume and stock return volatility. This specifies that stock price changes in any direction have information content for upcoming trading activities. There is no evidence of causality between stock returns and trading volume in either direction. It is evident from the analysis that influence of lagged stock returns on trading volume is insignificant.

Table 9 goes here

The table-9 shows the results for the VDC analysis. The variance decomposition technique for a period of 10 months ahead indicates that the Indian stock market is affected by trading volume. The variability of trading volume is explained by the shocks to stock return is 99% at 10 lags. The role of stock returns increase from 0.6% in the beginning of the period to 7.6% at the end of the period. In sum, the evidence supports the influential role of the trading volume on the Indian stock market. The results provide strong evidence in support of the argument that the movements of stock returns are explained by their own shocks rather than the shocks to the trading volume. The variability of stock return is explained by the shocks to trading volume is 99% at 10 lags. The role of trading volume increases from 7% in the beginning of the period to 10% at the end of the period. The variance decomposition analysis provides the evidence of past shock returns in predicting future trading volume.

Table 10 goes here

Figure 3 goes here

To further investigate the dynamic responses between the trading volume and stock return, the impulse response of the VAR system has been calculated and exhibited in the table-10and fig-3. It is observed from the table 10 that a one standard error shock in stock return affects trading volume negatively till around 10 months while one standard- error shock in trading volume affects stock market positively till around 10 months. Both impulse responses fall between the respective standard error bands. We find evidence of distinct asymmetry in the impulse responses between stock returns and trading volume. Shocks to trading volume do not tend to have significant impact on their corresponding returns. In stock markets, shocks to returns are important in predicting the future dynamics of their own return series and the future dynamics of their corresponding trading volume values. So the study revealed that shocks in stock returns impact trading volume in the expected direction over a short horizon.

CONCLUDING OBSERVATION

This study investigates the relationship between trading volume and stock returns using the data during January 2005 to January 2010. We found the evidence of significant contemporaneous relationship between return volatility and trading volume and indicate that information may flow simultaneously rather than sequentially into the market. Apart of it the study also found that trading volume is associated with an increase in return volatility and this relationship is asymmetrical. This implied that daily new information in market may have significant impact on price volatility. So the study indicates that bad news generate more impact on volatility of the stock return and trading volume. One explanation may be that normally investors have a higher aversion to downside risk, so they react faster to bad news. Additionally variance decomposition and impulse response function are also estimated to understand the dynamic relationship between stock return and trading volume. The study revealed that shocks in stock returns impact trading volume in the expected direction over a short horizon. But Co integration analysis shows that stock return volatility is co integrated with the trading volume indicating long-run equilibrium relationship. The error correction model also indicates the existence of a long-run causality between the stock return volatility and trading volume of the study. It is evident that that volatility moves in sympathy with trading activity in the primary market. Since existence of excessive volatility, or “noise,” undermines the usefulness of stock prices as a “signal” about the true intrinsic value of a firm, Investors, analysts, brokers, dealers and regulators are more concerned about stock return volatility. So the past information of trading volume is useful to improve the prediction of stock price volatility suggests that regulators and traders can use past information for monitoring volatility level in the market. So it suggests that the authorities can focus more on domestic economic policies to stabilize the stock market. One of the limitations of the study is that we have employed the traditional Granger –Causality test. Since it is now recognized that the conventional procedure may be inadequate, conclusions based on such an approach may yield misleading inferences. However the findings of the study are subject to the period of the study selected and the result may change if the study period will change.

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Table(s) and Figure(s)

Table 1: Augmented Dickey-Fuller, PP Test & KPSS Unit Root Test

variable	ADF Test	DF-GLS Test	PP Test	KPSS (LM stat)
R	-11.30398	-4.722975	-31.06757	0.184359
V	-0.160904	-0.444803	-11.67192	0.401354
R^2	-6.046182	-4.389949	-35.86743	0.049851

Note: ADF critical values with an intercept and no trend are: -3.436, -2.864 and -2.568 at 1%, 5% and 10% levels; PP critical values are: -3.436, -2.864 and -2.568 at 1%, 5% and 10% respectively. KPSS critical values are: 0.739, 0.463, and 0.347 at 1%, 5%, and 10% levels, DF-GLS critical values are -2.567,-1.941,-1.617 at 1%, 5% and 10% levels. Null of stationarity is accepted if the tests statistic is less than the critical value.

Figure 1: Daily Stock Returns (2005-2010)

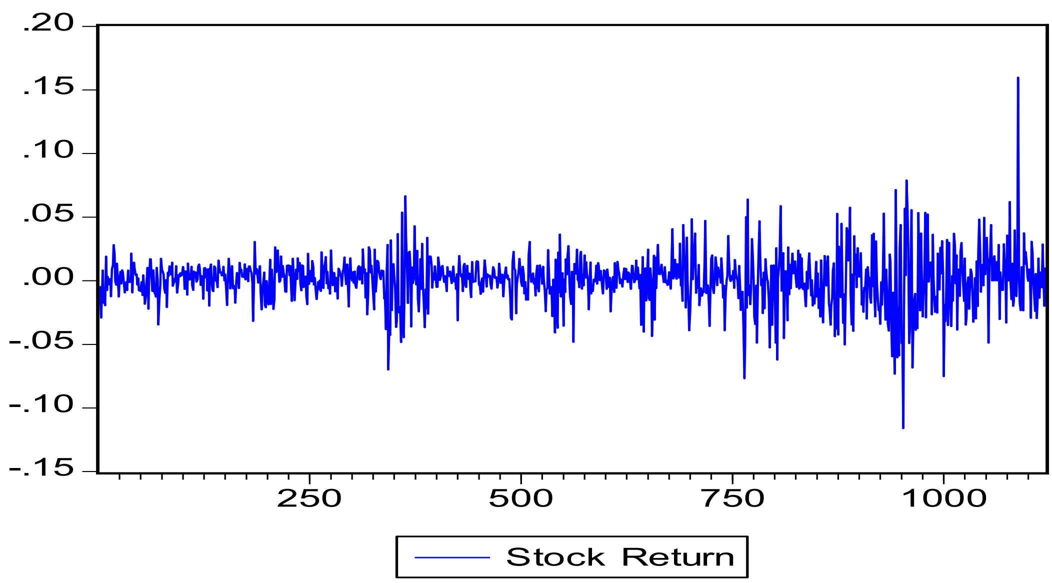

Figure 2: Daily Volume Change (2005-2010)

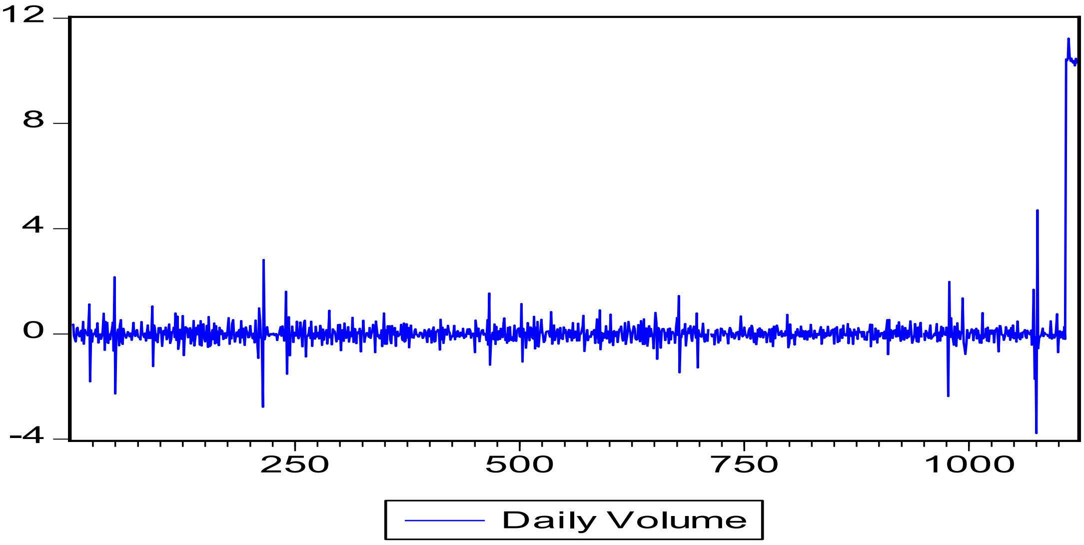

Table-2 Descriptive Statistics

	V	R	R^2	V_1
Mean	0.122853	0.000772	110.4779	0.113532
Median	0.000000	0.001536	0.000703	0.000000
Maximum	11.23585	0.159900	15937.65	11.23585
Minimum	-3.778490	-0.116044	0.000000	-3.778490
Std. Dev.	1.195232	0.019886	1156.270	1.155778
Skewness	7.564556	0.108384	10.59874	7.780010
Kurtosis	66.04969	8.979364	115.2817	70.43326
Jarque-Bera	194442.1	1655.740	603863.9	221507.9
Probability	0.000000	0.000000	0.000000	0.000000

Table-3 Contemporaneous relationship between stock returns and trading volume

$R_t = \alpha_o + \alpha_1 V_1 + \alpha_2 V_{t-1} + \alpha_3 R_{t-1} + u_t$

	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*
α_0	*0.000695*	*0.000599*	*1.160220*	*0.2462*
α_1	*-0.000404*	*0.000819*	*-0.494024*	*0.6214*
α_2	*0.000169*	*0.000847*	*0.199878*	*0.8416*
α_3	*0.077793*	*0.029984*	*2.594495*	*0.0096**

*Significant at 1%

Diagnostic Statistics

Adjusted R-squared	*0.003699*
Log likelihood	*2784.386*
Durbin-Watson stat	*1.994615*
Akaike info criterion	*-4.996201*
Schwarz criterion	*-4.978179*
F-statistic	*2.376220*
Prob(F-statistic)	*0.068502****

Table-4 Contemporaneous relationship between stock returns and trading volume

$$V_t = \beta_o + \beta_1 R_1 + \beta_2 R_{t-1} + \beta_3 V_{t-1} + v_t$$

	Coefficient	Std. Error	t-Statistic	Prob.
β_o	0.020743	0.018993	1.092140	0.2750
β_1	-0.849749	0.950411	-0.894086	0.3715
β_2	0.425692	0.026012	16.36510	0.0000*
β_3	0.525985	0.027010	19.47406	0.0000*

**Significant at 1%*

Diagnostic Statistics

Adjusted R-squared	0.722528
Log likelihood	-1059.916
Durbin-Watson stat	2.162013
Akaike info criterion	1.915240
Schwarz criterion	1.933289
F-statistic	964.4680
Prob(F-statistic)	0.000000

Table-5 Contemporaneous relationship between squared stock returns volatility and trading volume

$$V_t = \alpha_o + \phi_1 V_{t-1} + \phi_2 V_{t-1} + \alpha_1 R_t^2 + \alpha_2 D_t R_t^2 + v_t$$

	Coefficient	Std. Error	t-Statistic	Prob.
α_o	0.010097	0.018748	0.538533	0.5903
$Ø_1$	0.162950	0.037883	4.301426	0.0000*
$Ø_2$	0.151786	0.048090	3.156306	0.0016*
α_1	0.064302	0.006944	9.259897	0.0000*
α_2	-788.0575	2000.862	-0.393859	0.6938

**Significant at 1%*

Diagnostic Statistics

Adjusted R-squared	*0.742102*
Log likelihood	*-1018.775*
Durbin-Watson stat	*2.029977*
Akaike info criterion	*1.842980*
Schwarz criterion	*1.865541*
F-statistic	*799.5074*
Prob(F-statistic)	*0.000000*

Table-6 Johansen's Co integration test

Assumptions: No deterministic trend in the series in levels and no intercept in the co integrating equation

Variable	Eigen-value	Trace Statistic	0.05 Critical Value (p-value)	Maximum Eigen statistics	0.05 Critical Value (p-value)	Hypothesized No. Of CE (S)
Stock return volatility	0.256893	329.2738*	12.32090 ((0.0001)	328.3879	11.22480(0.0001)	None *
Trading volume	0.000801	0.885877	4.129906 (0.4008)	0.885877	4.129906(0.4008)	At most 1

Trace test indicates 1 co integrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

Table -6a Unrestricted Adjustment Coefficients (alpha)

Stock return volatility	0.011473	-1.91E-05
Trading volume	0.003836	0.017594
Log Likelihood	1740.372	

Table- 6b Normalized co integrating coefficients (standard error in parenthesis)

Stock return volatility	Trading volume	Log Likelihood
1.0000	6.92E-05 (0.00059)	1740.372

Table-7 Vector Error Correction Estimates

List of Variables	CointEq1
Trading volume	1.000000
Stock return volatility (t-statistics) (P-value)	65747.55 (3911.21) [16.8100]
C	-25.95026

List of Variables	Trading volume	Stock return volatility
EC_{t-1} (t-statistics) (P-value)	0.000128 (0.00040) [0.31999]	-1.11E-05 (6.6E-07) [-16.8056]
Trading volume $_{t-1}$ (t-statistics) (P-value)	-0.649736 (0.02970) [-21.8763]	-3.63E-05 (4.9E-05) [-0.73894]
Trading volume $_{t-2}$ (t-statistics) (P-value)	-0.173131 (0.02972) [-5.82543]	2.65E-05 (4.9E-05) [0.53853]
Stock return volatility $_{t-1}$ (t-statistics) (P-value)	5.359149 (22.9197) [0.23382]	-0.199650 (0.03793) [-5.26339]
Stock return volatility $_{t-2}$ (t-statistics) (P-value)	-6.130637 (17.0741) [-0.35906]	-0.091029 (0.02826) [-3.22142]
C(Constant) (t-statistics) (P-value)	0.017162 (0.01875) [0.91537]	-9.13E-06 (3.1E-05) [-0.29420]

Determinant resid covariance (dof adj.)	4.13E-07
Determinant resid covariance	4.09E-07
Log likelihood	4995.732
Akaike information criterion	-9.008557
Schwarz criterion	-8.945158

Table-8 Pair-wise Granger Causality Tests between stock return volatility and trading volume

Null Hypothesis:	F-value	P-values
	0.30927	0.73404
Stock Return(R) does not Granger Cause Trading volume (V)	0.14707	0.86325
Trading volume(V) does not Granger Cause Stock return (R)		

Stock return volatility(R^2)does not Granger Cause Trading volume (V) Trading volume(V) does not Granger Cause Stock return volatility(R^2)	6.87293* 315.837 *	0.00108 4.E-109

Table-9 Variance decomposition of stock return and trading volume

Lag(n)	% of the movement in the volume explained by the shocks to:		% of the movement in the stock return explained by shocks to:	
	volume	Stock return	Stock return	volume
1	100.0000	0.000000	99.92973	0.070270
2	99.99404	0.005956	99.90427	0.095733
3	99.95684	0.043157	99.90150	0.098497
4	99.94875	0.051249	99.89989	0.100105
5	99.93963	0.060371	99.89989	0.100113
6	99.93490	0.065101	99.89943	0.100568
7	99.93057	0.069431	99.89938	0.100623
8	99.92757	0.072430	99.89917	0.100827
9	99.92501	0.074986	99.89907	0.100927
10	99.92301	0.076988	99.89893	0.101066

Table-10 Impulse Response function

Period	Stock return volatility	volume
1	0.000000	-0.000526
2	-0.005286	-0.000320
3	-0.016140	0.000107
4	-0.010505	-8.00E-05
5	-0.012497	5.53E-06
6	-0.010779	-4.25E-05
7	-0.011171	-1.48E-05
8	-0.010428	-2.85E-05
9	-0.010313	-1.99E-05
10	-0.009874	-2.35E-05

Fig-3